DOCUMENT RESUME

ED 261 063 TM 850 453

AUTHOR Burkhalter, Bettye B.; And Others
TITLE Anomalies in Auditing the Compensation Function: Getting Two Sets of Answers from One Set of Data.
PUB DATE [83]
NOTE 29p.; Small print in tables 2-5.
PUB TYPE Reports - Research/Technical (143)

EDRS PRICE MF01 Plus Postage. PC Not Available from EDRS.
DESCRIPTORS Comparative Analysis; *Correlation; Individual Characteristics; Mathematical Models; *Multiple Regression Analysis; *Path Analysis; *Personnel Evaluation; Personnel Management; *Predictor Variables; *Salaries; Salary Wage Differentials; Statistical Studies
IDENTIFIERS *Audits

ABSTRACT

To examine and clarify background conditions for understanding variables which affect salary, the salary and compensation programs at two industrial and three educational organizations were subjected to a statistical audit. Data were available on 272 employees. Ten compensation variables were studied as having direct or indirect effects on salary: sex, race, military service, educational attainment, relevant experience, organization (industrial or educational), years of service, performance history, salary grade and time in grade. These variables were labeled independent variables for a multiple regression analysis. Path analysis was also performed, with these variables labeled causal. A third model for statistical analysis emerged, which deleted the variable, time in grade. A bivariate correlation matrix was prepared for the third statistical technique. The most important variables, based on multiple regression, were organization, grade, years of service, and military service. Based on path analysis, they were organization, educational level, military service, and grade. Results suggested that current path analytic methods are more effective than multiple regression. (GDC)

**********
* Reproductions supplied by EDRS are the best that can be made *
* from the original document. *
**********

ED261063



# Anomalies in Auditing the Compensation Function: Getting Two Sets of Answers From One Set of Data

Bettye B. Burkhalter, James Noel Wilmoth, and James A. Buford, Jr.

Auburn University

Nathan L. Essex

The University of Alabama

U.S. DEPARTMENT OF EDUCATION
NATIONAL INSTITUTE OF EDUCATION
EDUCATIONAL RESOURCES INFORMATION CENTER (ERIC)

☒ This document has been reproduced as received from the person or organization originating it.

☐ Minor changes have been made to improve reproduction quality.

• Points of view or opinions stated in this document do not necessarily represent official NIE position or policy.

"PERMISSION TO REPRODUCE THIS MATERIAL IN MICROFICHE ONLY HAS BEEN GRANTED BY

B. B. Burkhalter

TO THE EDUCATIONAL RESOURCES INFORMATION CENTER (ERIC)."

Running head: AUDITING THE COMPENSATION FUNCTION

TM 850 453

BEST COPY AVAILABLE

Abstract

The purpose of this study was to examine and clarify background conditions for understanding variables which affect salary. Federal court decisions, professional literature, and emerging national issues suggest that reliable statistical methods will become increasingly important in auditing the compensation function. This study used a linear causal model based on path analytic procedures to analyze the direct and indirect effects and effect coefficients of ten theoretically related variables on salary. Although path analysis is relatively new in compensation audits, it is believed defensible models subjected to path analysis offers an alternative to the more widely used multiple regression techniques.

## Anomalies in Auditing the Compensation Function: Getting Two Sets of Answers From One Set of Data

There are several issues involved in the most effective approach to evaluating sources of variation for the compensation audit. Among them, one issue involves the choice of market data versus organizational data for testing with the statistical model. A second issue involves the choice of approach: multiple or stepwise regression (order of entry determined by the statistical package) versus structural model building. Holmes (1983) pointed out a third problem or issue: If the analysis must be defended in court, how may it be made comprehensible to lawyers and judges, few of whom understand the intricacies presented by statistical experts?

Statistical audits of compensation programs may be accomplished in many ways depending on the organization's resources and level of sophistication. Although in their specifics they are not equally sensitive and powerful, multiple regression analysis, stepwise regression, path analysis, and sequential regression analysis are probably the most sensitive and powerful procedures available today to compensation professionals. In encouraging personnel management to consider the statistical audit, Sullivan (1982) cautioned:

> It seems certain that most large employers can expect one or more statistical audits of their pay programs on the part of agencies charged with the enforcement of the EEO statutes in the years ahead. Thus, it behooves these employers to conduct their own audits lest they be surprised or embarrassed by their own data. (p. 21)

In preparing for such audits, this study treated the assumption that present methodologies for auditing the compensation function are quite controversial and often inadequate. Multiple regression, the most widely used statistical method, as presently employed, is often misapplied in resolving compensation problems. These shortcomings are emphasized by the absence of prior policy statements that are sufficiently comprehensive to reveal theoretical connections among the related compensation issues and the assumptions concerning associations among the variables under study. The result is often answers to questions which may be correct from the standpoint of how the study is designed, but often inappropriate or misleading in terms of both weak causal relationships and implications for corrective action.

Since the underlying theory of compensation is well established (Odiorne, 1979), the adoption of a more sophisticated analytical approach is warranted. Thus, the major purpose of this study was to compare two statistical methods for auditing compensation programs. A secondary purpose was to examine and clarify contributions of antecedent variables affecting salary.

## Methods

### Research Setting and Subjects

The data for this research were collected from 272 full-time employees at two industrial and three educational organizations in the southeastern region of the United States. A letter was sent to eight prospective organizations inquiring about the nature of their personnel system and their interest in participating in an empirical study to audit their compensation programs. Selection of the five final organizations was based on the following criteria: (a) identification and ordering of compensated variables, (b) a sufficient number of subjects to permit meaningful statistical analysis, (c) a personnel management system containing accurate employee data, (d) a willingness to supply data from subjects at the middle management level, and (e) availability for the most recent five years of valid performance appraisal data for each subject.

The organizations maintain a self-professed policy of employing, assigning, and advancing employees on the basis of ability, physical capacity, education, and experience without regard to race, creed, color, religion, age, national origin, or sex. All organizations attempt to select, train, assign, transfer, and promote those individuals who are best qualified by virtue of skill, experience, education, and personal

characteristics to meet the requirements of current openings without discrimination.

Variables Under Study

Ten compensation variables were selected as having direct or indirect effects on salary. These variables were labeled "independent" (IVs) in regression analysis studies, and labeled "causal" in path analytic studies. The ten antecedent variables selected were sex, race, military service, educational level, related experience, organization, years of experience, performance history, grade, and time-in-grade. The variable to be explained was salary. Table 1 contains data which present these variables with their codebook values and units of measure as utilized in this study.

---

Table 1 about here

---

Data Analysis

Data were analyzed using the Statistical Package for Social Sciences (SPSS) and the Statistical Analysis System (SAS) computer packages in a manner consistent for the proposed models. The path analysis, beginning with Model I as shown in Figure 1, included three iterations, each iteration containing the following four sequential stages: computation of partial correlations on all paths hypothesized to have path coefficients of zero, adjustment

of model to include paths whose hypothesized zero coefficients statistically were different from zero, verification that paths hypothesized to have non-zero path coefficients did have, and readjustment of model to delete paths whose hypothesized non-zero

---

Figure 1 about here

---

coefficients statistically did not differ from zero. Direct-, indirect-, and effect-coefficients were computed for the final model and were converted to dollar equivalents. Both standardized regression coefficients and corresponding dollar equivalents were produced for comparison with the path analytic coefficients.

## Results

This paper covers two general types of results. The first type is a description of two statistical techniques (path analysis versus multiple regression) for the research question, "What variables (sex, race, performance, etc.) contribute information helpful to understanding salaries paid to the 272 individuals in the sample?" The second type is a report of descriptive statistics (correlations) on variables included in the study.

### Path Analysis Results

Partial correlations and path coefficients associated with Figure 1 are presented in Table 2. The partial correlations are in the upper triangular portion of the table and are indexed by

corresponding column headings and row stubs. Variables to the left in the headings represent the variables controlled in the partial correlation of any entry. For example, the ".024" in the first row, seventh column, is the partial correlation between "SEX" and "YRSVC" with "RELEXP" partialled out. Since "SEX" is one of the variables named in the correlation it is not partialled out.

---

Table 2 about here

---

Except for cells indexed with "(b)" all of the partial correlation entries are statistically nonsignificant as they should be in the absence of linkages in the path analytic "SAL" model of Figure 1. Stated differently, when there are no specification errors, the partial correlation for each omitted linkage statistically should be nonsignificant. Thus, partial correlations are the statistical checks that linkages omitted in the model should, in fact, be omitted. Furthermore, those linkages indexed with "(b)" represent paths that should be added to the model according to evidence at this stage of analysis.

Path coefficients are in the lower triangular area of Table 2, and are presented in the same format as the partial correlations. All relevant path coefficients for a model component are entered in the row having the same name as the

column heading. The row stub and column heading, when the same, represent a subsequent variable in a component of the path analytic model. For example, for the component to the subsequent variable "EDLEV" one is concerned with the 4th row stubbed "EDLEV" to the 4th column headed "EDLEV" containing three nonempty cells in the "SEX," "RACE," and "MILSVC" columns. The value, .132, entered in the "SEX" to "EDLEV" cell represents the path coefficient from "SEX" (antecedent) to "EDLEV" (subsequent). Thus, an entry in any lower triangular cell of the table represents a direct linkage between an antecedent variable named in the corresponding heading and the subsequent variable in the stub.

But, "EDLEV" as a subsequent variable contains three path coefficients in the lower triangular portion: one for each arrow pointing to "EDLEV" in the path diagram for Model I as shown in Figure 1. In order to know what variables are controlled in computing any specific path coefficient, the other entries in a row must be noted. Each occupied cell in the row of a stub assists in defining a possible controlled variable for the path coefficient involving that stub as a subsequent variable. All occupied cells in a row of the lower triangular matrix, except the focal cell, indicate headings specifying the controlled variables. In the "EDLEV" example, two of the variables in the row are controlled in path coefficient calculations involving the third

variable. For "RELEXP" as a subsequent variable the path coefficient from "MILSVC" is the same as the bivariate regression beta (correlation coefficient) since no other variable is controlled.

A linkage was hypothesized initially from "RACE" to "MILSVC." That path coefficient is -.092 significant at the .122 level (df = 269). A level of significance for a path coefficient larger than .05 indexed with "(c)" in the lower triangular portion of the matrix indicates a specification error in the model; that is, it indicates that the corresponding path for the cell should be deleted. With first the addition of 12 paths from too large partial correlations and deletion of 8 paths from too small path coefficients, Model II as presented in Figure 2 emerged from Model I.

---

Figure 2 about here

---

It is possible that a particular partial regression coefficient is large enough to require addition of a path whose path coefficient is too small for it to be retained. Such a contradiction should be examined closely under guidance of the theoretical formulation promoting development of the model. Contradictions are consequences of multicollinearity and represent potential problems in unraveling the real influence of each variable on the statistically formulated compensation function.

Furthermore, it is multicollinearity arising out of common antecedent variable accountability for effects on subsequent variables that is at the root of the anomaly that will be developed in more detail below.

The Linear Causal Model II component of Table 3 suggests statistical coherence for the model. However, there exists a problem of conceptual coherence. After the transition between Model I and Model II there was not a large enough path coefficient between "TIMEINGR" and "SAL" to retain the "TIMEINGR" path. The small partial correlation, .041 in cell (e) of Model II, vindicates the earlier decision to delete the "TIMEINGR" path. While evaluating Model II, Model III emerges under the current decision to delete entirely the variable "TIMEINGR" and the six linkages from its antecedent variables as shown in Figure 3.

---

Figure 3 and Table 3 about here

---

Predictably, deleting "TIMEINGR" from the 10th position in the model deletes all entries in the Model II "TIMEINGR" (10th) row and (10th) column of Table 3. Had "TIMEINGR" occurred earlier in a model having a high degree of multicollinearity, its deletion would have produced both partial correlation and path analytic coefficient changes requiring expansion of Table 3 to include a Linear Causal Model III component.

Bivariate Correlation Results

A bivariate correlation matrix for all variables in Model III and their correlation-related effect coefficients from path analysis is presented as Table 4. One should interpret the three entries in each cell of the lower triangular reproduced correlation portion as direct effects (top entries) and indirect effects (middle entries) added together to equal effect coefficients (bottom entries). For comparative purposes it is the effect coefficients that should be balanced against their respective bivariate correlation coefficients.

---

Table 4 about here

---

Means and standard deviations in the bottom two rows of Table 4 are used in converting beta and effect coefficients (coef) based on standardized data into corresponding dollar equivalents ($EQ) for raw data. The equation for this purpose is

$$\$ \text{ Equivalent} = (\text{Std. Data Effect}) * (S_y/S_j)$$

Path Analysis Versus Multiple Regression for Compensation Audits

With the techniques of partial correlation and multiple regression analysis, it is possible to adjust a theoretically defensible compensation model in such a way that the result is

parsimonious, verifies the theory, and reflects fundamental differences in compensation within levels and between variables studied. Table 5 permits specific comparisons of bivariate, path analytic, and multiple regression analyses in terms of comparable standardized data coefficients and of their translations into dollar equivalents. Although compensation is regarded as a phenomenon determined by a multiplicity of associated variables, the bivariate portion of the table is presented for completeness. Relative importance of the independent variables using betas from multiple regression techniques can be ordered as follows: ORGAN (.846), GRADE (.276), YRSVC (.109), MILSVC (.095), SEX (-.085), EDLEV (-.079), RELEXP (.074), PRFHSTY (.070), and RACE (-.029). Relative importance of the independent variables using effect coefficients from path analysis techniques can be ordered as follows: ORGAN (.777), EDLEV (.627), MILSVC (.367), GRADE (.293), YRSVC (.243), PRHSTY (.115), SEX (-.074), RACE (-.047), and RELEXP (.038). TIMEINGR was deleted in adjusting to Model III.

---

Table 5 about here

---

The Anomaly

Of greater interest are the specifics for the results that vary between the path analytic and the multiple regression analyses. For initial comparisons one should examine the effect

coefficient columns against the corresponding regression coefficient columns of Table 5. MILSVC generates an effect coefficient about 3.9 times as large as its corresponding regression coefficient ($2,124.61 vs. $547.92). The effect coefficient for RACE is about 1.6 times as large as its regression coefficient (-$1,317.76 vs. -$810.66). On the other hand, the multiple regression coefficient for RELEXP is about 2.0 times as large as its effect coefficient. Of further interest are the differences implicitly required in interpreting results from the two approaches: three variables (RACE, EDLEV, and RELEXP) by path analysis yield only indirect effects suggesting that these variables operate on SAL through their correlations with other variables between them and SAL in Model III. SEX, on the other hand, seems to operate on SAL such that a part of its direct effect (-$1,218.31) is counterbalanced with an indirect effect of opposite sign ($32.06). Also interesting is the path analytic equivalent of $2,442.92 (all indirect) for EDLEV against the -$308.38 regression outcome: results that are contradictory in interpretation.

## Discussion and Recommendations

Results of this study support the growing body of professional literature which suggests that a more effective statistical methodology is needed to examine wage differences. If one model encompasses factors that clarify the compensation issues

in personnel management more effectively than another model, it should be recommended as the more appropriate. The results of this study not only support the need for auditing compensation functions, but also the use of linear causal modeling and path analysis as an effective auditing tool over the widely used multiple regression technique. When one considers that often the primary purpose of the auditing process is to identify SEX and RACE inequities, path analysis is superior to other regression techniques in terms of more precisely delineating problems.

This study also clearly exemplifies a misapplication of multiple regression correlation analysis by personnel professionals under an assumption that multiple regression correlates offer the best basis for correcting or compensating for discrepancies in SAL caused by given variables (e.g., RACE). When an organization compensates for RACE under multiple regression, the organization in fact treats RACE and all other independent variables as exogenous variables. In effect, this treatment does not detect indirect influences through endogenous variable linkages as is the case when the model is recognized as being at least weakly causal, thus path analytic.

In the widely used multiple regression sense, the standardized data partial regression coefficient for RACE ( $\beta$ = -.029) generates the softest possible assignment to the variable. When direct and indirect effects are computed on RACE, assignment

is realized only through indirect effects since the sum of direct ($\underline{d}$ = .000) and indirect ($\underline{i}$ = -.047) effects equal the total effect ($\underline{e}$ = -.047). In short, multiple regression claims linkage of RACE to SAL to be direct whereas path analysis shows it to be indirect only. Using the multiple regression methodology, however, if there is going to be any compensation at any time in SAL due to the effects of RACE, compensation would be according to the regression coefficient ( $\beta$ = -.029) and would certainly be in an improper amount.

Taking each numerically weighted path in Model III and moving unidirectionally, it becomes quite evident that each of the variables plays a significant role and may influence SAL directly and/or indirectly. Although the multiple regression technique accounts for approximately 86% of the variability, only about 25% is assignable unambiguously to the independent variables, leaving about 61% unassigned in commonality--a ratio of 2.33 unassigned to 1 assigned. It appears that a model having such a high ratio could lead to potential erroneous action by the personnel administrator.

Demonstrably, partitioning of variance in regression situations is not to be recommended. Rather, the compensation professional is advised to convert regression or effect coefficients to their dollar equivalents for policy decisions. A more complete decomposition of observed bivariate correlations

occurs with much more computing effort. In any case, results are model specific in that changes in the ordering of variables or design of the linkages potentially can affect the computed outcomes.

Adjustments of effect coefficients for antecedent endogenous variables should be approached with caution because of the usual multicollinear complexities of the corresponding decompositions of modeled correlation coefficients. Conversely, the compensation administrator may, without impunity, adjust bias out of antecedent exogenous variables--in this case, SEX and RACE. Adjustments for bias reflected in two or more coefficients are done with computational difficulty. Necessary are decompositions of all associated bivariate correlations and zeroing of terms containing correlations rendered insignificant by the adjustments. Alternatively, an effect can be adjusted, then new path analytic coefficients can be computed and studied before adjusting for additional sources of bias.

In this study multiple regression proved unacceptable as an explanatory technique for the compensation function because it contains roughly two times (2.33) as much unassigned variability (commonality) as assigned (uniqueness) and because its independent variables may be modeled in the way they influence each other.

It is important to note, however, in order to test and improve the statistical probabilities of this study, it is

recommended that a larger sample comprising at least 1,000 participants be used, thereby permitting the inclusion of all possible two-way interaction effects and selected three-way interaction effects. Researchers using the multiple regression technique should exercise more data discipline (e.g., equal numbers of male, female, black, white, etc.) than imposed in the present study.

## References

Holmes, R. A. (1983, July). Comparable worth and wage discrimination: Two years after Gunther v. County of Washington. Paper presented for presentation at the Wage Discrimination/Comparable Worth Seminar. Washington, DC: Author (pp. 1-27).

Odiorne, G. S. (1979. Personnel management for the '80s. The Personnel Administrator, 24, 77-80.

Sullivan, J. L. (1982). Maintaining a sound pay program. A presentation at the American Society for Personnel Administration/American Compensation Association/ Equal Employment Advisory Council Conference--"Comparable Worth: A Team Approach." Comparable Worth: A Team Response to the Issues. Scottsdale, AZ: American Compensation Association, American Society for Personnel Administration, International Personnel Management Association, and the Equal Employment Advisory Council.

## Author Notes

Bettye B. Burkhalter, Ph.D., is the Special Assistant to the Vice President for Research and Associate Professor in the Department of Educational Leadership at Auburn University in Alabama.

James Noel Wilmoth, Ph.D., is Associate Professor in the Department of Foundations of Education at Auburn University in Alabama.

James A. Buford, Jr., Ph.D., is accredited by the American Personnel Institute and is a Management Scientist and Coordinator of Management Development in the Alabama Cooperative Extension Service at Auburn University in Alabama.

Nathan L. Essex, Ph.D., is Professor and Chairman of Administration and Planning in the Area of Administration and Educational Leadership at The University of Alabama in University, Alabama.

Table 1

Codebook Values and Units of Measurement for

Variables in Compensation Study

| Variable Label | Variable Name | Unit of Measurement |
|---|---|---|
| 1. SEX | Sex | Male = 1, Female = 2 |
| 2. RACE | Race | White = 1, Black = 2, Other = 3 |
| 3. EDLEV | Education Level | 0 = No HS Degree, 1 = No Degree, 2 = No HS but Trade, 3.00 = No Degree, 3.20, 3.30 = HS & Trade School, 3.45, 3.55 = HS & Some College, 4 = B.S., 5 = M.S., 6 = Specialist or 6 Year, 7 = Doctorate, 8 = Post Doctorate |
| 4. MILSVC | Military Service | Years and tenths--active service only |
| 5. RELEXP | Related Experience | Years and tenths of related professional experience |
| 6. ORGAN | Organization | Industrial or Educational |
| 7. YRSVC | Years of Service | Years and tenths since initial appointment |
| 8. PRFHSTY | Performance History | Use last three years: 0-1.9 = unsatisfactory, 2.0-3.9 = marginal, 4.0-5.9 = satisfactory, 6.0-7.0 = excellent, 8.0-10 = outstanding |
| 9. GRADE | Grade | Professor = 4, Associate Professor = 3, Assistant Professor = 2, Instructor = 1, Other = 5 |
| 10. TIMEINGR | Time in Grade | Years and tenths since promotion. If entry level leave blank. |
| 11. SAL | Salary | Twelve month equivalent |

**Table 2**

**Partial Correlation Coefficients (Upper Triangular) and Path Coefficients (Lower Triangular) for Linear Causal Models in the Statistical Compensation Function for SAL**

**Linear Causal Model I**

| KEY: Partial Corr. *(df)* Significance | 1. SEX | 2. RACE | 3. MILSVC | 4. EDLEV | 5. RELEXP | 6. ORGAN | 7. YRSVC | 8. PRFHSTY | 9. GRADE | 10. TIMEINGR | 11. SAL |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. SEX | | *(d)* | | | .062<br>(267)<br>.307 | | .024<br>(265)<br>.699 | .001<br>(264)<br>.985 | −.270*(b)*<br>(186)<br>.000 | .110<br>(185)<br>.135 | |
| 2. RACE | *(d)* | | | | .007<br>(267)<br>.910 | | | −.095<br>(264)<br>.123 | −.202*(b)*<br>(186)<br>.005 | | |
| 3. MILSVC | −.248<br>(269)<br>.000 | −.092*(c)*<br>(269)<br>.122 | | | | | .097<br>(266)<br>.112 | .036<br>(264)<br>.564 | −.076<br>(186)<br>.302 | −.128<br>(185)<br>.080 | .214*(b)*<br>(184)<br>.003 |
| 4. EDLEV | .132<br>(268)<br>.034 | −.093*(c)*<br>(268)<br>.126 | .156<br>(268)<br>.013 | | −.051<br>(267)<br>.405 | | −.213*(b)*<br>(265)<br>.000 | | .305*(b)*<br>(186)<br>.000 | .245*(b)*<br>(185)<br>.001 | −.123<br>(184)<br>.094 |
| 5. RELEXP | | | .158<br>(270)<br>.002 | | | | | .200*(b)*<br>(264)<br>.001 | .367*(b)*<br>(186)<br>.000 | .409*(b)*<br>(185)<br>.000 | .138<br>(184)<br>.061 |
| 6. ORGAN | .101<br>(266)<br>.009 | .044*(c)*<br>(266)<br>.239 | .183<br>(266)<br>.000 | .750<br>(266)<br>.000 | −.095<br>(266)<br>.012 | | | | | −.399*(b)*<br>(185)<br>.000 | .720*(b)*<br>(184)<br>.000 |
| 7. YRSVC | | .030*(c)*<br>(267)<br>.585 | | −.324<br>(267)<br>.000 | .056*(c)*<br>(267)<br>.307 | .668<br>(267)<br>.000 | | | | .264*(b)*<br>(185)<br>.000 | .209*(b)*<br>(184)<br>.004 |
| 8. PRFHSTY | | | | .081*(c)*<br>(267)<br>.378 | .195<br>(267)<br>.001 | .219<br>(267)<br>.028 | .148<br>(267)<br>.020 | | | .067<br>(185)<br>.360 | |
| 9. GRADE | −.211<br>(264)<br>.000 | −.159<br>(264)<br>.000 | | .427<br>(264)<br>.000 | .300<br>(264)<br>.000 | −.642<br>(264)<br>.000 | .391<br>(264)<br>.000 | .118<br>(264)<br>.024 | | | |
| 10. TIMEINGR | | .101<br>(265)<br>.054 | | .384<br>(265)<br>.000 | .405<br>(265)<br>.000 | −.739<br>(265)<br>.000 | .286<br>(265)<br>.000 | | −.244<br>(265)<br>.000 | | |
| 11. SAL | −.080<br>(263)<br>.003 | .024*(c)*<br>(263)<br>.340 | .117<br>(263)<br>.000 | | | .783<br>(263)<br>.000 | .111<br>(263)<br>.000 | .076<br>(263)<br>.005 | .288<br>(263)<br>.000 | .032*(c)*<br>(263)<br>.224 | |

**Note.** Cells having an *a* or *b* index paths added to Model I for path coefficient analysis under the criteria *a* = (p .05) and *b* = (p .01). Cells having a *c* index path deleted for Model II due to nonsignificance of the path. The cells labeled *d* index unanalyzed correlations between exogenous variables. Empty cells index hypothesized linkages in the upper triangular and nonhypothesized linkages in the lower triangular.

Table 3

**Partial Correlation Coefficients (Upper Triangular) and Path Coefficients (Lower Triangular) for Linear Causal Models in the Statistical Compensation Function for SAL**

**Linear Causal Model II**

| KEY: Partial Corr. *(df)* Significance | 1. SEX | 2. RACE | 3. MILSVC | 4. EDLEV | 5. RELEXP | 6. ORGAN | 7. YRSVC | 8. PRFHSTY | 9. GRADE | 10. TIMEINGR | 11. SAL |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. SEX | | *(d)* | | | .062<br>(267)<br>.307 | | .024<br>(265)<br>.699 | .001<br>(264)<br>.985 | | .110<br>(185)<br>.135 | |
| 2. RACE | *(d)* | | −.094<br>(269)<br>.123 | −.100<br>268<br>.103 | .007<br>(267)<br>.910 | .078<br>(266)<br>.205 | .037<br>(265)<br>.543 | −.095<br>(264)<br>.123 | | | −.077<br>(184)<br>.297 |
| 3. MILSVC | −.260<br>(270)<br>.000 | | | | | | .074<br>(265)<br>.228 | .036<br>(264)<br>.564 | −.076<br>(186)<br>.302 | −.128<br>(185)<br>.080 | |
| 4. EDLEV | .123<br>(269)<br>.048 | | .164<br>(269)<br>.009 | | −.051<br>(267)<br>.405 | | | .043<br>(264)<br>.485 | | | −.123<br>(184)<br>.094 |
| 5. RELEXP | | | .188<br>(270)<br>.002 | | | | .044<br>(265)<br>.471 | | | | .138<br>(184)<br>.061 |
| 6. ORGAN | .106<br>(267)<br>.006 | | .179<br>(267)<br>.000 | .746<br>(267)<br>.000 | −.094<br>(267)<br>.012 | | | | | | |
| 7. YRSVC | | | | −.323<br>(269)<br>.000 | | .662<br>(269)<br>.000 | | | | | |
| 8. PRFHSTY | | | | | .199<br>(268)<br>.000 | .288<br>(268)<br>.000 | .135<br>(268)<br>.028 | | | .067<br>(185)<br>.360 | |
| 9. GRADE | −.211<br>(264)<br>.000 | −.159<br>(264)<br>.001 | | .427<br>(264)<br>.000 | .300<br>(264)<br>.000 | −.642<br>(264)<br>.000 | .391<br>(264)<br>.000 | .118<br>(264)<br>.024 | | | |
| 10. TIMEINGR | | .101<br>(265)<br>.054 | | .384<br>(265)<br>.000 | .405<br>(265)<br>.000 | −.739<br>(265)<br>.000 | .286<br>(265)<br>.000 | | −.244<br>(265)<br>.000 | | .041*(e)*<br>(184)<br>.581 |
| 11. SAL | −.076<br>(265)<br>.004 | | .118<br>(265)<br>.000 | | | .771<br>(265)<br>.000 | .113<br>(265)<br>.000 | .080<br>(265)<br>.002 | .293<br>(265)<br>.000 | | |

**Note.** Cells having an *a* or *b* index paths added to Model I for path coefficient analysis under the criteria *a* = (p .05) and *b* = (p .01). Cells having a *c* index path deleted for Model II due to nonsignificance of the path. The cells labeled *d* index unanalyzed correlations between exogenous variables. Empty cells index hypothesized linkages in the upper triangular and nonhypothesized linkages in the lower triangular. On cell *e* hinges the transition to Model III: Both the TIMEINGR row and column are deleted.

Table 4

Observed Correlations (Upper Triangular); Direct-, Indirect-, and Effects-Coefficients (Lower Triangular); Means; and Standard Deviations for the Over-Identified, 10-Variable Model III

| VARIABLE | 1. SEX | 2. RACE | 3. MILSVC | 4. EDLEV | 5. RELEXP | 6. ORGAN | 7. YRSVC | 8. PRFHSTY | 9.† GRADE | 11. SAL |
|---|---|---|---|---|---|---|---|---|---|---|
| 1. SEX | | .124 | −.260 | .080 | .006 | .119 | .058 | .024 | −.245 | −.078 |
| 2. RACE | | | −.123 | −.096 | −.005 | −.037 | .036 | .098 | .201 | .134 |
| 3. MILSVC | −.260<br>.000<br>−.260 | .000<br>.000<br>.000 | | .132 | .188 | .233 | .185 | .165 | .075 | .373 |
| 4. EDLEV | .123<br>−.043<br>.080 | .000<br>.000<br>.000 | .164<br>.000<br>.164 | | −.011 | .780 | .194 | .279 | .031 | .637 |
| 5. RELEXP | .000<br>−.049<br>−.049 | .000<br>.000<br>.000 | .188<br>.000<br>.188 | .000<br>.000<br>.000 | | .068 | .014 | .181 | .365 | .150 |
| 6. ORGAN | .106<br>.018<br>.124 | .000<br>.000<br>.000 | .179<br>.105<br>.284 | .746<br>.000<br>.746 | −.094<br>.000<br>−.094 | | .411 | .330 | .148 | .819 |
| 7. YRSVC | .000<br>.056<br>.056 | .000<br>.000<br>.000 | .000<br>.135<br>.135 | −.323<br>.494<br>.172 | .000<br>−.062<br>−.062 | .662<br>.000<br>.662 | | .256 | .227 | .534 |
| 8. PRFHSTY | .000<br>.033<br>.033 | .000<br>.000<br>.000 | .000<br>.138<br>.138 | .000<br>.238<br>.238 | .199<br>−.036<br>.164 | .288<br>.089<br>.378 | .135<br>.000<br>.135 | | .191 | .437 |
| 9.† GRADE | −.211<br>−.034<br>−.245 | −.159<br>.000<br>−.159 | .000<br>.013<br>.013 | .427<br>−.384<br>.044 | .300<br>.055<br>.356 | −.642<br>.304<br>−.338 | .391<br>.016<br>.407 | .118<br>.000<br>.118 | | .247 |
| 11. SAL | −.076<br>.002<br>−.074 | .000<br>−.047<br>−.047 | .118<br>.250<br>.367 | .000<br>.627<br>.627 | .000<br>.038<br>.038 | .771<br>.006<br>.777 | .113<br>.130<br>.243 | .080<br>.035<br>.115 | .293<br>.000<br>.293 | |
| Mean | 1.272 | 1.070 | 0.551 | 4.691 | 5.757 | 3.312 | 7.375 | 6.375 | 2.302 | $22,331.82 |
| Std. Dev. | .446 | .255 | 1.235 | 1.834 | 6.363 | 1.528 | 6.849 | 1.787 | .928 | $ 7,149.57 |

Note. †Variable 10 (Time-In-Grade) is omitted from Model III.

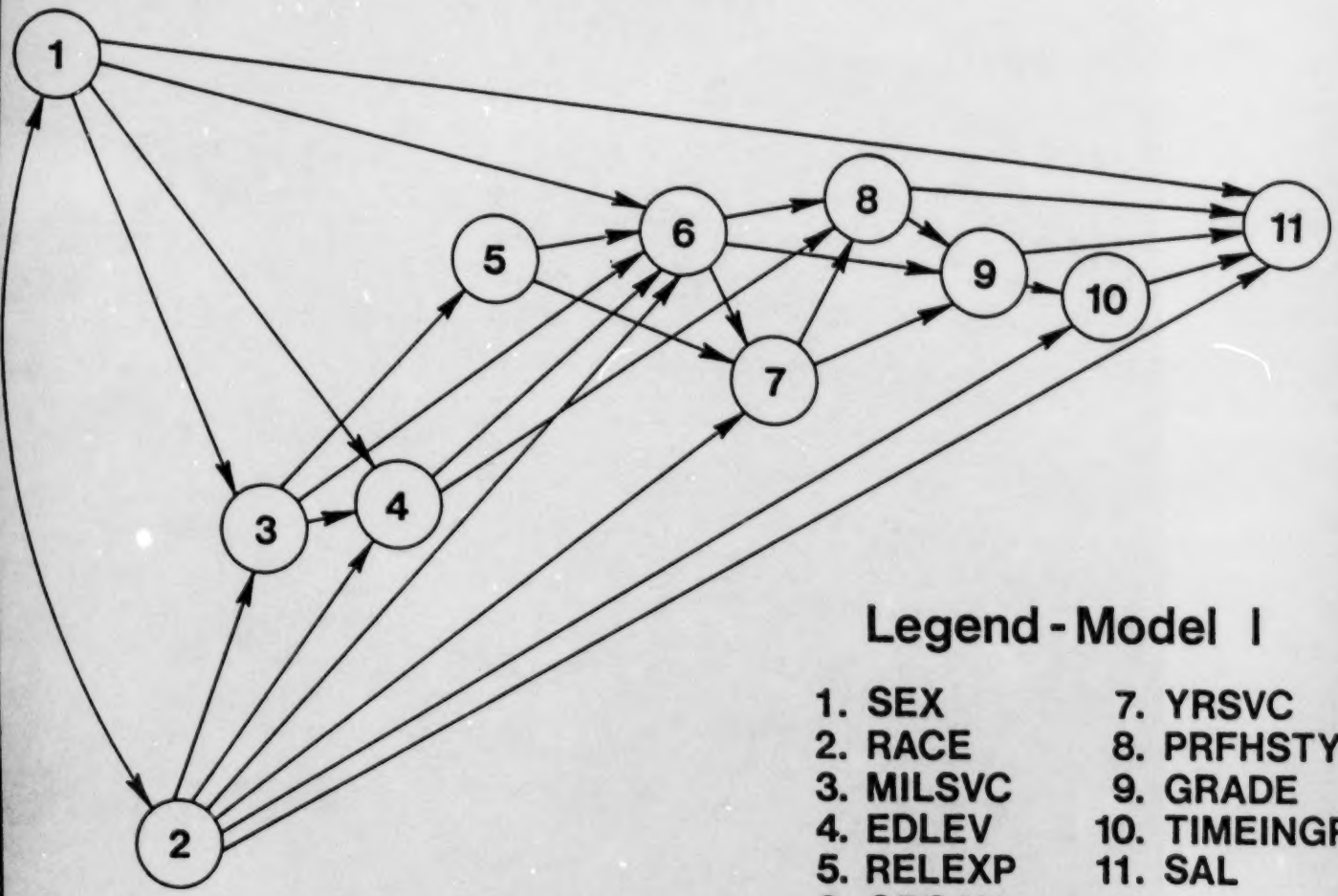
Table 5

Bivariate, Path Analytic, and Multiple Regression Coefficients with Dollar Equivalents for Relationships of Variables Influencing Salary

| Variable Name | Bivariate | | Path Analytic | | | | | | Multiple Regression | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Direct | | Indirect | | Effect | | | | | |
| | Coeff. r | $ | Coeff. | $ | Coeff. | $ | Coeff. | $ | Coeff. (Beta) | $ | Std. Err. B | $R^2$ When Last |
| 1. SEX | -.078 | -1250.37 | -.076 | -1218.31 | .002 | 32.06 | -.074 | -1186.25 | -.085 | -1356.84 | 415.55 | .0060 |
| 2. RACE | .134 | 3757.03 | .000 | -- | -.047 | -1317.76 | -.047 | -1317.76 | -.029 | - 810.66 | 686.05 | .008 |
| 3. MILSVC | .373 | 2159.34 | .118 | 683.12 | .250 | 1447.28 | .367 | 2124.61 | .095 | 547.92 | 152.49 | .0067 |
| 4. EDLEV | .637 | 2481.89 | .000 | -- | .627 | 2442.93 | .627 | 2442.93 | -.079 | - 308.38 | 159.48 | .0020 |
| 5. RELEXP | .150 | 168.54 | .000 | -- | .038 | 42.70 | .038 | 42.70 | .074 | 83.61 | 29.77 | .0042 |
| 6. ORGAN | .819 | 3832.13 | .771 | 3607.54 | .006 | 28.07 | .777 | 3635.61 | .846 | 3959.66 | 220.14 | .1776 |
| 7. YRSVC | .534 | 557.43 | .113 | 117.96 | .130 | 135.70 | .243 | 253.66 | .109 | 113.70 | 30.68 | .0078 |
| 8. PRFHSTY | .437 | 1748.38 | .080 | 320.07 | .037 | 148.03 | .115 | 460.10 | .070 | 278.95 | 104.23 | .0042 |
| 9. GRADE | .247 | 1902.96 | .293 | 2257.35 | .000 | -- | .293 | 2257.35 | .276 | 2125.91 | 236.01 | .0444 |
| INTERCEPT: | | | | | | | | | | $4595.94 | 1291.08 | -- |

**Figure 1**

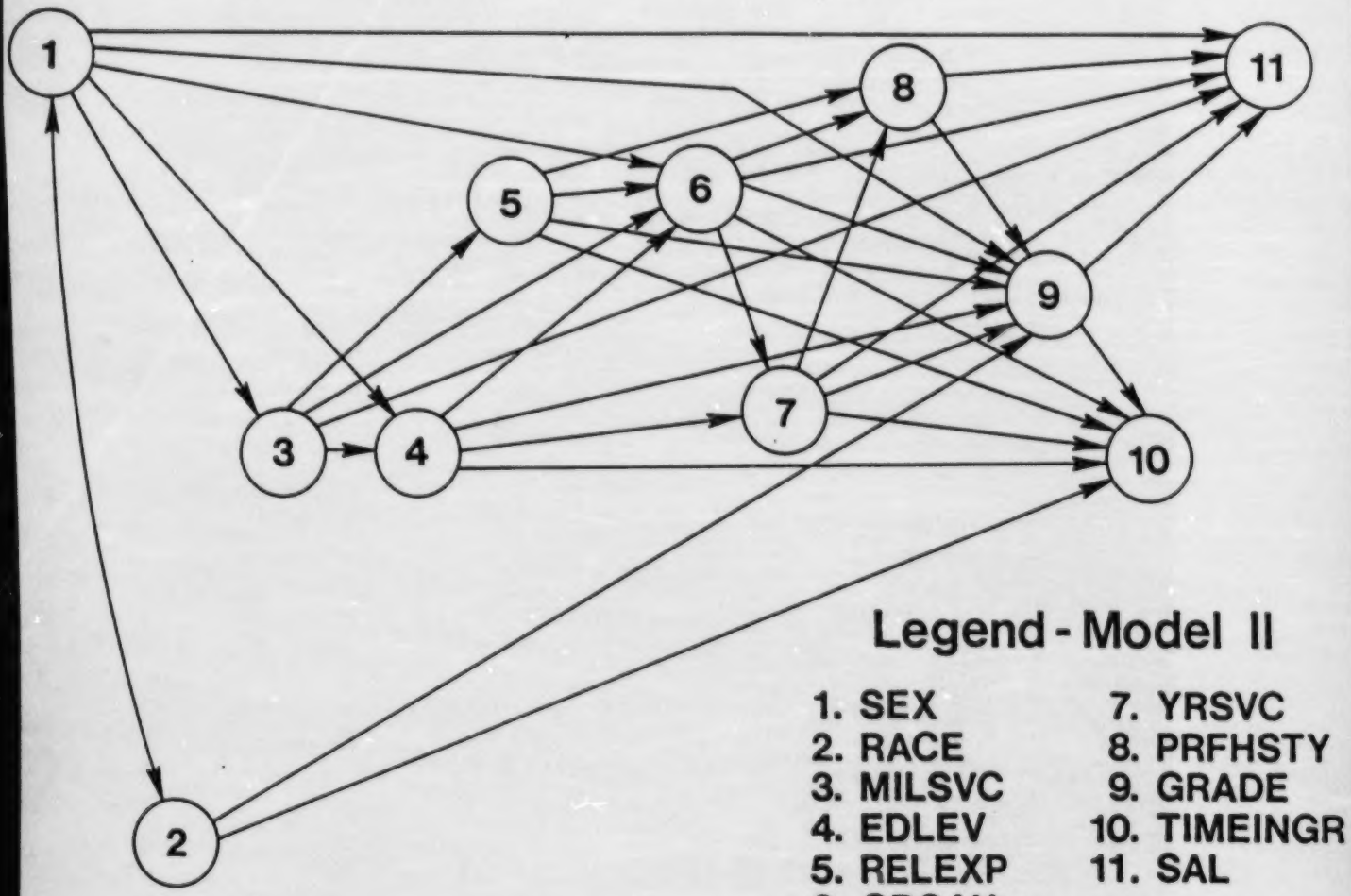
**Model I for SAL. Linkages index non-zero path coefficients. Non-linkages index hypothesized partial correlations of zero. Residuals are not modeled.**




## Legend - Model I

1. SEX
2. RACE
3. MILSVC
4. EDLEV
5. RELEXP
6. ORGAN
7. YRSVC
8. PRFHSTY
9. GRADE
10. TIMEINGR
11. SAL

Figure 2
Model II for SAL. Linkages index non-zero path coefficients. Non-linkages index partial correlations of zero. Residuals are not modeled.




**Legend - Model II**

1. SEX
2. RACE
3. MILSVC
4. EDLEV
5. RELEXP
6. ORGAN
7. YRSVC
8. PRFHSTY
9. GRADE
10. TIMEINGR
11. SAL

Figure 3

Model III for SAL. Linkages index non-zero path coefficients. Non-linkages index partial correlations of zero. Residuals are not modeled. TIMEINGR as variable is not included in Model III.